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ABSTRACT

The analysis of previously obtained data concerning short-term visual memory and cognition by a method suggested by Tucker is proposed. Although interesting individual differences undoubtedly exist in people's ability and capacity to process short-term visual information, studies have not generally examined these differences. In fact, conventional analyses have used group means which destroy the investigation of individual differences. Previous research by the authors indicates substantial and reliable changes in the abilities a group of subjects uses to process information as the stimulus itself subtly changes. These changes that an individual manifests have, however, been obscured until now. The proposed method by Tucker simultaneously analyzes the differences among subjects and describes the complexity of the stimulus. Thus the behavior of a single individual to a visual stimulus can be summarized and analyzed in light of other abilities he may possess. Tucker's method can estimate practice and fatigue effects on a task. Finally, the experience gained herein with the Tucker method should prove useful, in that it could be an alternative way of analyzing individual differences other than the regression approach. (Author)

FINAL REPORT

Analysis of Cine-Psychometric Visual Memory Data by the Tucker Generalized Learning Curve Method

National Institute of Education Project No. 3-0244

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Introduction

Several writers have recogrized that learning curves based on mean performance over time obscure demonstrable and reliable individual differences. (See Duncan, 1960; Glaser, 1967; and Gulliksen, 1968). Merrell (1931) was among the first to point out that if learning curves of some individuals or subgroups differ significantly from the mean curve, then the mean curve does not adequately represent some, and perhaps many, individuals' performance. Citing three studies that pointed out difficulties in using group or average learning curves, Gulliksen (1974) commented that despite such cautions, most researchers obtain only a single set of parameters. He indicated that it would indeed be interesting if all individuals had the same learning curve, but then unity could be ascertained only by finding individual learning curves and then determining that they differed only by random error. Hall (1971, pp. 31-32) offers similar cautions.

One main problem can thus be stated as follows: is there a methodology that produces individual learning curves, determines which individual learning curves do not differ significantly from each other and can therefore be combined, and determines which individual learning curves do differ significantly from each other. Such a methodology would not treat all individual learning curves as if they were exactly alike. The answer to this problem is yes, a suitable methodology has been described independently by two eminent statisticians.

Tucker (1958, 1959, 1960, 1966) and Rao (1958) both described a

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factor analytic procedure that can be applied to learning data to determine whether a single mean curve adequately represents performance for all subjects or whether subjects' performance is more accurately represented by two or more learning curves. Tucker and Rao showed that factor analysis could be applied to analyze the abilities operating at different stages in a learning task, or any task of a sequential nature.

Messick (1972) reviewed four studies that used factor analytic procedures to describe changes in learning over time and further suggested that factor analysis could be used to analyze differential traits in problem solving and creativity tasks, if appropriate sequential measures were obtained.

These applications differ from conventional uses of factor analysis. Factor analysis traditionally describes a small set of traits described by a larger set of tests. Factor scores are also conventionally used as independent variables in a multiple regression equation to reduce the number of variables, and factor techniques are used when canonical correlations between sets of variables are obtained.

The following explanation of the less-conventional use of factor analysis to analyze learning data is based on Tucker (1960, 1966). Tucker's method represents a solution to the problem of determining how many learning curves are required to describe the performance of a group of subjects on a task, curves that at the same time preserve information on individual differences.

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Summary

From the ideas well set forth by Ferguson (1954), Messick (1972) and others, we sought a method that would identify different abilities that entered at different stages in a task. The method selected should meet Cronbach's (1957) criterion that it would consider individual differences as well as group performance. Tucker's (1960, 1966) method seemed able to identify differing abilities while at the same time preserve individual differences.

Using Kaiser's (1974) Little Jiffy Mark IV to skirt the problem of scaling and of difficulty factors, we factor analyzed two film tests and found essentially two factors operating in each test. Had the task been longer (some authors recommend 1000 items) we likely might have found more factors; it is equally likely, however, that diminishing returns would soon obtain.

It seems that the results are stable across various factor analytic methodologies, a requirement first proposed by Harris (1967) and repeated again, with a different emphasis, in 1973 (Dziuban and Harris, 1973). Second, the greatest advantage for using the Mark IV rather than one of the other methods presented here lies in the availability of the measure of sampling adequacy, a reflection of how well the data fit Guttman's requirement that the inverse of the correlation matrix be diagonal. The MSA's for STVM II part 1 and STVM III part 1 were mediocre and middling. Since the input matrix was a binary data matrix,

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His method involves factoring a trials by subjects data matrix. If the task is simple, only one factor might appear, but more complex tasks presumably require more factors to explain the variance.

Tucker's method is based on the factor analytic equation

$$x_{ji} = a_{j1} + j_{j2}y_{2i} + \cdots$$

where x_{ji} is the score on trial j for individual i, the a's are coefficients depending on trials, and the y's are individual parameters. The a's are constant for all subjects on any given trial, whereas the y's vary across individuals on any given trial. The a's can thus be thought of as a matrix of factor loadings and the y's as a matrix of factor scores.

Tucker's method indicates a task's complexity, or the number of different curves required, by the number of factors that result. The method also indicates how individuals differ on abilities used at different stages in the given task. If, for example, a subject receives a high factor score on the first factor and near-zero scores on others he may be said to be a pure exemplar of factor I. In contrast, subjects with significant factor scores on all factors that define a given trial can be said to have more complex methods of cognition. Thus, factor scores indicate how one individual's functioning differs from another's.

Although the Tucker factor analytic procedure may be applied to any sequential data, the present report describes the procedure as applied

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to sequential data from two motion picture tests. This report differs from earlier studies that used Tucker's method not only in the stimulus material used, but also by the use of Kaiser's scale-free Little Jiffy Mark IV (Kaiser and Rice, 1974; Kaiser, 1974) to solve the problem of which input matrix to use.

Our own previous work combining correlational and experimental methods consisted primarily of a series of separate factor analyses to differing stimuli of a large reference battery in combination with short-term visual memory abilities (Seibert and Snow, 1965; Seibert, Reid and Snow, 1967). We had two striking results, both of which were replicated: the abilities involved in certain of the short-term memory tasks change markedly within a total time span of .5 second (i.e., the "aptitudes" important in extremely short-term memory, say, one one-hundredth second, are different from those for longer durations of, say, one-half second) and also that a novel ability factor, named "serial integration" or "temporal closure" is among the factors which show varying involvement in short-term memory performances. Our findings of short-term aptitude change over time relate closely to Fleishman's work (e.g., 1967).

These separate factor analyses to differing visual stimuli did not analyze the task complexity, nor did they permit a thorough analysis of individual differences in processing visual information.

Thus, although the main problem was to ascertain what learning

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curves existed in a specific sequential task and to see if individual learning curves differed from the mean curve, two lesser problems also needed attention. The first of these was the interpretation of the individual or subgroup learning curve, once it was obtained. It was desired to determine to what extent would specific learning curves be correlated with certain cognitive and information processing abilities.

The second sub-problem concerned the influence of the design of the stimulus material on acquisition. In the present study, the stimulus was a 2 x 4 or a 2 x 3 array of letters or of colored objects, one of which was to be chosen as "correct." It was thought, for example, that letters or objects at the left side or at the top of the tachistoscopically-presented stimulus would be learned more readily than letters at the right side, or at the bottom.

The purpose of the present study was to analyze learning curves derived from two film tests of short term visual memory, using Kaiser's Little Jiffy Mark IV, to determine if individual learning curves differed from mean learning curves for such a short term visual memory task, and to characterize the resulting factors by their correlations with marker variables. It was finally desired to determine the effect of various stimuli characteristics on performance.

Review of related research

Tucker's factor-analytic method has been used in studies of proba-

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bility matching (Harris, 1971; Wainer, 1968), of consumer purchasing behavior for particular products (Sheth, 1969), of comparing the discrimination of rats and fish (Weitzman, 1959, 1963), for examining subjects' learning by an anticipation method (Frederiksen, 1969), from comparing concept information, paired associate, and rote memory tasks (Duncanson, 1964, 1966), and to ascertain differences in cardiac responses (Van Egeren, 1972). These studies used a variety of input matrices (e.g., sum of squares and cross products or correlations) and took various approaches to the rotation problem. An alternate manova approach to analyzing learning curves was suggested by Patthof and Roy (1964).

Kaiser's Little Jiffy Mark IV is more appealing than other exploratory factor analytic methods that have typically been used for several reasons. First, as Guttman (1954, 1956) points out, the inverse input correlation matrix, R^{-1}, should be nearly diagonal for factor analysis to be appropriate. Also, Kaiser and Rice (1974), with an assist from Meyer and Olkin, developed a normalized measure of sampling adequacy (MSA), which has a range of zero to one, and gives a numerical appreciation of how well the data satisfy Guttman's principle. If the normalized MSA is $<.50$, then the data are unacceptable, but as the data more nearly satisfy Guttman's principle, the MSA approaches 1.0. In 1962, Harris wrote an important paper demonstrating that if certain input matrices are rescaled by S^{-1}, where $S^2 = (\text{diag } R^{-1})^{-1}$, then component

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analysis, common factor analysis, and image analysis all produce identical eigenvector matrices, which means that they produce the same factors. This led Kaiser to state his principle that "It don't make no never mind," i.e., don't worry whether to factor a sums of squares and cross products matrix, covariance matrix, or correlation matrix; avoid the issue by using a scale-free method of factor analysis (Kaiser, 1970). The Mark IV is scale free, since it uses Kaiser's image analysis (Kaiser, 1963; Reid, 1968) as its point of departure. Third, it has been shown by Lord (1955) that factor analysis of an item intercorrelation matrix of binary variables that have low intercorrelations is not likely to produce artifactual difficulty factors. At any rate, the Little Jiffy Mark IV would not seem to produce such artifactual factors, since the analysis is of images, the predicted value of each variable from all others, and images are multivariate normal.

The history of motion picture testing, or cine-psychometry, has been reviewed elsewhere (Gibson, 1947; Seibert and Snow, 1965; Seibert, 1971a; Seibert 1971b; see also McDaniel, 1971; McDaniel, 1973). The idea of using tests on film dates back to 1942 and many of its ideas originated with J. J. Gibson, J. C. Flanagan, and F. A. Geldard. An item on a motion picture test can be either static (in which case the advantage of the film format is limited to the precise timing of the presentations and duration of the stimulus) or the film item can be dynamic, as with items comprising the automobile driving tests present-

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ed on CBS television a few years ago.

The final objective of stimulus complexity is important since studies in visual cognition and short-term memory demonstrate that success in the processing of visual information depends not only upon traits inherent in the individual, but also upon the design characteristics of the visual stimulus material.

For example, Mackworth (1963) reported that the number of digits correctly identified increases sharply as exposure duration increased from 30 to 50 milliseconds, but that greater exposure durations had little effect upon correct identification. Averbach and Coriell (1961) reported that memory for tachistoscopically presented characters in an array varies, depending on whether specific characters (or elements) are marked or designated for recall with a circle or with a bar, particularly at certain crucial delay intervals. They also suggested that a two-stage memory process, involving first a short term and vulnerable storage of visual information, then a long term storage, accounts for the observed performances. The work of Fleishman (e.g., 1967) and Cattell (1971) also involve the concept of stimulus complexity. An apt summary is provided by Neisser (1966).

Procedure

159 college students took two motion picture tests. The first test, Short Term Visual Memory II (STVM-II) had 64 items, or eight eight-item

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subtests (Seibert, Reid and Snow, 1967). In each item, an 8 letter, 2 x 4 array was presented tachistoscopically for about .031 second. A black circle marker then appeared to mark one of the eight array positions, and Ss were to record the letter occupying the designated position. The marker could precede the array by .052 second or follow it by .01, .094, .177, .260, .344, .428, or .51 second. The second test, Short Term Visual Memory III (STVM-III) was similar, but had two markers to designate one array position for each item. Simultaneously with each 2 x 4 array, a black vertical bar marker appeared and then at intervals listed above, a circle marker appeared. K-R 20 reliabilities for STVM-II and III have been reported as .81 and .90 (Seibert, Reid and Snow, 1967).

In addition, 13 other tests were administered as a reference battery: First and Last Names, Digit Span--Visual, Gestalt Completion, Wide Range Vocabulary, Advanced Vocabulary, Color Form Recognition, Film Sequence Memory A and B, Picture Identification, Successive Perception III and IV, and Position Recall II and III. (Those familiar with the French, Ekstrom and Price's Kit of Reference Tests will recognize most of these tests; all are described in Seibert, Reid and Snow (1967)).

Factor analyses of the two 159 x 8 binary matrices were accomplished by means of Kaiser's Little Jiffy Mark IV (Kaiser, 1970; Kaiser and Rice, 1974). Factor scores were obtained, and factor loadings and the factor

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scores of selected individuals were plotted.

To define further the obtained factors, and to characterize individuals receiving high or low factor scores, regression analyses were run using as independent variable the scores from the 13 tests in the reference battery, and as dependent variables, factor scores from the two motion picture tests.

Finally, to determine the effects of varying stimuli characteristics, regression analyses were run for Short Term Color Memory I and II (see Appendix) and STVM II and III item preferences, using part score, location, and name of stimulus as independent variables.

Results

A Little Jiffy Mark IV on STVM II part 1 resulted in an overall root mean square of .14, a measure of sampling adequacy (MSA) of .61, and an index of factorial simplicity (IFS) of .83. The MSA would be characterized as "mediocre" and the IFS as "meritorious." Table 1 shows the rotated factor solution.

Insert Table 1 about here

Factor I might be described as late learning, Factor II as early learning only or fatigue and Factor III as being befuddled except at initial and final stages.

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A Kaiser image analysis (Kaiser, 1963; Reid, 1968) resulted in three factors associated with eigenvalues of one or greater. Varimax rotated factor loadings appear in Table 2.

Insert Table 2 about here

A Little Jiffy (a principal components solution followed by a varimax rotation of all factors associated with eigenvalues of one or greater) also produced three components, which are detailed in Table 3.

It was felt that difficulty factors would not be a problem since the overall root mean square was .14.

Insert Table 3 about here

Figure 1 shows factor loadings plotted for each of the eight items in STVM II part 1. Figure 2 shows the conventional learning curve based on item preferences. The conventional learning curve is based on item preferences. The conventional learning curve completely obscures the fatigue factor.

Insert Figures 1-6 about here

Figures 3 through 6 show learning curves of four typical subjects with different factor scores. Figure 3 represents the performance of

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a subject with a low factor I score and a high factor II score. (Factor scores have been rescaled to a mean of 50 and a standard deviation of 10.) The low score on factor I indicates that the subject is not a late learner, and the high score on factor II means that the subject starts out well, which are borne out by the graph. Figure 4 shows the performance of a subject with low scores on all factors; the graph shows that he got none of the items right. Figure 5 shows a learning curve for a subject high on both factors; he got most of the items right, as expected. Figure 6 shows a learning curve for a subject scoring high on factor 1 and low on factor 2; his learning curve illustrates his description, based on his factor scores, as a late learner.

To gain a further appreciation for the factors obtained from the application of Tucker's technique to STVM II, each of the three factor score vectors was used in turn as the dependent variable in a stepwise regression with 13 other tests that had been administered to the subjects at the same time as STVM II. These 13 tests were First and Last Names, Digit Span Visual, Gestalt Completion, Wide Range Vocabulary, Advanced Vocabulary, Color Form Recognition, Film Sequence Memory A and B, Picture Identification Successive Perception III and IV, and Position Recall II and III. Only Picture Identification had a worthwhile correlation ($r = .40$) with factor scores on factor 1. Somewhat similar to a Gestalt completion task, the Picture Identification test is also an important variable in the serial integration factor (Seibert, Reid

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and Snow, 1967).

Thus subjects who succeeded early in the STVM II task tended to do so by tapping a trait or process somewhat similar to serial integration or Gestalt completion; whether or not subjects also responded correctly to the items in the second half of the test depended largely upon whether or not they made use of the trait or process described by factor II.

The application of Little Jiffy Mark IV to STVM III part 1 resulted in an overall root mean square of .26, a measure of sampling adequacy of .76, and an index of factorial simplicity of .95. The MSA could be described as "middling" and the IFS as "marvelous." Table 4 shows the rotated factor solution.

Insert Table 4 about here

Factor I might be called late learning and Factor II early learning only or perhaps fatigue.

A Kaiser image analysis resulted in three factors associated with eigenvalues of unity or greater; the third factor can be tossed. A tendency to overfactor is characteristic of this method. The rotated (varimax) solution is in Table 5.

Insert Table 5 about here

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This is essentially the same factor pattern as the Little Jiffy Mark IV only less clearly defined.

A Little Jiffy, probably the most common "factor analysis" performed in the literature, resulted in a similar pattern as shown in Table 6.

Insert Table 6 about here

A maximum likelihood solution (Jöreskog and van Thillo, 1971) was also applied, and produced similar results to the other solutions except that the factors were switched (see Table 7).

Insert Table 7 about here

Figure 7 shows the factor loadings plotted for each of the eight items in STVM part 1. Figure 8 shows the conventional learning curve based on item preferences. Note that the conventional curve masks the two underlying processes. Figures 9 through 12 show learning curves of four typical subjects with different factor scores.

Insert Figures 7-12 about here

Figure 9 shows the performance of a subject who is high on factor I and low on factor II; accordingly the graph of his performance indicates

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that he missed the first two items and got the remaining six items correct. Figure 11 shows the performance of a subject somewhat the opposite of the subject in Figure 9. The subject in Figure 11 had a low factor I score and a high factor II score.

Each of the two factor score vectors was in turn used in a stepwise regression with the 13 tests mentioned before as independent variables. Picture Identification was again the only test with a worthwhile correlation; it correlated .39 with both factor I and factor II scores. Thus, success in the STVM III part 1 test seems to have depended somewhat on an ability similar to serial integration or Gestalt completion.

So far Tucker's method has been applied to the analysis of learning curves to two different film tests to support the idea that different abilities exert different effects at different stages of learning. For these data, it has been shown that the mean learning curve obscured individual differences in processing visual information. We have also attempted to describe these different abilities by a set of 13 aptitude tests.

Finally, three specific stimulus characteristics are related to item preference. Although this report so far has concentrated on one part of STVM II and one part of STVM III, each test had eight parts. One stimulus characteristic was number of delay frames, each set of which defined a part. A second characteristic was that different letters were randomly selected for each item. Third, the correct answer

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could be in any of 8 positions in the 2 x 4 array of letters.

Accordingly, regression analyses were run on item preferences of STVM II and III with parts, positions, and letters as dependent variables to measure the proportion of variance accounted for by these three stimulus characteristics.

A multiple regression equation with 26 letter vectors, 8 position vectors, and 1 part vector, with item preferences of STVM II as the dependent variable produced an $R^2 = .71$, or a shrunken $\hat{R}^2 = .37$. A similar equation but with the part vector dropped gave an $R^2 = .70$ or $\hat{R}^2 = .37$. (See Tables 8 and 9.) An F test between these two models of course was not significant, which meant that part (that is, number of delay frames) played no important role in accounting for variance in item preference.

Insert Tables 8 & 9 about here

An equation with the 26 letter vectors alone gave an R^2 of .33 with item preference, but the unbiased estimate, $\hat{R}^2$, shrunk to zero. (See Table 10.) Interesting differences occurred in the partial sums of squares among certain letters, but this discussion can be saved for another time.

An equation with the 8 position vectors alone gave an R^2 of .50, $\hat{R}^2 = .41$. (See Table 11.) Thus, position in the array accounted for

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41% of the variance of item preferences.

Insert Tables 10 & 11 about here

A multiple regression equation with 26 letter vectors, 8 position vectors, and 1 part vector, with item preferences of STVM III as the dependent variable gave an R^2 of .73, or $\hat{R}^2$ = .42. A similar equation but without the part vector gave an R^2 of .71, or $\hat{R}^2$ = .38. (See Tables 12 and 13.) An F ratio between these two models was 2.68 (1, 29) which is not significant. Thus, as in STVM II, part again played no important role in accounting for variance of item preferences.

Insert Tables 12 & 13 about here

An equation with the 26 letter vectors alone gave an R^2 of .42, but $\hat{R}^2$ shrunk to zero. A regression equation with the 8 position vectors alone produced R^2 = .45 or $\hat{R}^2$ = .37. (See Tables 14 and 15.) As in STVM II, position in the array accounted for 37% of the item preference variance.

Insert Tables 14 & 15 about here

It is interesting to compare the influence that position has in these two tests with two other film tests, Short Term Color Memory

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(STCM) I and II which used a 2 x 3 stimulus array presenting 6 colors from a pool of 9.

A multiple regression equation with 9 color vectors, 6 position vectors, and one part vector with item preference for STCM I as the dependent vector produced an $R^2 = .72$, or $\hat{R}^2 = .61$. A similar equation only without the part variable produced an $R^2 = .71$, or $\hat{R}^2 = .61$. (See Tables 16 and 17.) Thus the variable of part (the number of frames the stimulus remains on the screen) had no predictive value to item preference at least in the 4 to 12 frames range.

Insert Tables 16 & 17 about here

A model using only the 9 color vectors as independent variables produced an $R^2 = .57$, or $\hat{R}^2 = .48$. (See Table 18.) An F ratio run between the regression model with position and color vectors and the model with color vectors only produced an F (5, 40) = 2.60, which was significant at the .05 level. Thus both color and position made significant contributions to the variance in item preference in STCM I.

Insert Table 18 about here

A multiple regression equation with 9 color vectors, 6 position vectors, and one part vector with item preference for STCM II as the

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dependent vector resulted in an R^2 = .73, or $\hat{R}^2$ = .63. When the part vector was dropped from the model, the R^2 was .66, or $\hat{R}^2$ = .54. (See Tables 19 and 20.) These two regression models produced an F ratio = 10.86 (df = 1, 39) which is significant at the .01 level.

Insert Tables 19 & 20 about here

When the regression model contained the part and color vectors, the R^2 = .64, or $\hat{R}^2$ = .55. (See Table 21.) The full model (R^2 = .73) compared with this model yielded an F (5, 39) of 2.56 which is significant at the .05 level. Thus, position made a significant contribution to the item preference variance.

Insert Table 21 about here

When the regression model contained both part and position vectors, the R^2 was .16, or $\hat{R}^2$ = .03. (See Table 22.) Thus color makes the most contribution to item preference variance, but part and position still make some contribution. In none of the other three tests in this report did part make significant contribution to item preference variance.

Insert Table 22 about here

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Summary

From the ideas well set forth by Ferguson (1954), Messick (1972) and others, we sought a method that would identify different abilities that entered at different stages in a task. The method selected should meet Cronbach's (1957) criterion that it would consider individual differences as well as group performance. Tucker's (1960, 1966) method seemed able to identify differing abilities while at the same time preserve individual differences.

Using Kaiser's (1974) Little Jiffy Mark IV to skirt the problem of scaling and of difficulty factors, we factor analyzed two film tests and found essentially two factors operating in each test. Had the task been longer (some authors recommend 1000 items) we likely might have found more factors; it is equally likely, however, that diminishing returns would soon obtain.

It seems that the results are stable across various factor analytic methodologies, a requirement first proposed by Harris (1967) and repeated again, with a different emphasis, in 1973 (Dziuban and Harris, 1973). Second, the greatest advantage for using the Mark IV rather than one of the other methods presented here lies in the availability of the measure of sampling adequacy, a reflection of how well the data fit Guttman's requirement that the inverse of the correlation matrix be diagonal. The MSA's for STVM II part 1 and STVM III part 1 were mediocre and middling. Since the input matrix was a binary data matrix,

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and intercorrelations of binary variables generally have a restricted range, the obtained MSA will be necessarily lowered. The MSA would increase as the number of variables, factors, and subjects increase, but for the present data, the greatest cause for the low MSA would likely be primarily due to the low intercorrelations. In general, the overall root-mean-square of the correlation matrix had to be .13 or more for the MSA to be at least .60. The MSA for the other seven parts of STVM II and III, and for the three parts each of STCM I and STCM II was generally unsatisfactory, indicating that the factor analytic approach was not acceptable for these data. This indication that these matrices were not appropriate for factor analysis would have been overlooked had conventional factor analytic techniques such as the Little Jiffy or classical factor analysis been used. Although other alternatives are available to test whether or not a matrix should be factor analyzed, at this time the MSA from the Mark IV seems clearly to be the best (Dziuban and Shirkey, 1974).

We have not discussed the problem of rotation in this report. It might be suggested that neither the Harris-Kaiser orthogonal--oblique rotation that the Mark IV uses, nor the varimax criterion following Kaiser image analysis is appropriate to the analysis of sequential learning data. We would agree that the characteristics of the learning curves reported herein which have several zero entries would be a function of the rotational algorithm. On the other hand, for these data,

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at least, it seems inappropriate to postulate a transformation matrix whereby all curves are monotonically increasing, as for example in Tucker (1966), as this postulate would negate the possibility that a subject could start out well, but become confused as the trials proceed, an entirely plausible hypothesis for these visual cognition tasks. Another paper (Reid and Seibert, in preparation) addresses the rotational problem in some detail. In brief, we suggest that the current optimum solution to the rotational problem of sequential learning data is to adopt a stance similar to that proposed by Wainer (1968) and Schönemann (1966). At any rate, this paper has demonstrated that more than one factor is needed to adequately describe the learning curves of the subjects in the study, and therefore it follows that a single mean learning curve is an inadequate representation of the individuals' performance.

We made some attempt to describe the obtained factors with other variables; at least one factor correlated with a variable similar to Gestalt completion or serial integration.

Finally we considered the effect of three stimulus characteristics upon item preference. Test part (number of stimulus frames, or number of delay frames) rarely accounted for an important part of item preference, whereas position in the array always did and color did in the two color tests.

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Table 1

Little Jiffy Mark IV on STVM II - 1

	Factor		
Item	I	II	III
1	-01	01	26*
13	03	25*	-08
22	-02	26*	08
32	-02	20*	11
38	31*	03	01
48	29*	05	-12
60	34*	-02	-01
62	29*	-05	14*

Table 2

Kaiser Image Analysis on STVM II - 1

	Factor		
Item	I	II	III
1	06	04	25
13	06	23	-04
22	04	25	06
32	05	20	12
38	31	09	09
48	26	09	-03
60	32	04	07
62	30	02	20

Table 3

Little Jiffy on STVM II - 1

	Factor		
Item	I	II	III
1	02	09	84
13	10	68	-28
22	02	72	07
32	00	60	35
38	65	10	09
48	61	14	-33
60	70	-04	03
62	59	-07	48

Table 4

Little Jiffy Mark IV on STVM III - 1

	Factor	
Item	I	II
5	-05	54*
6	-02	43*
24	12	40*
32	32	13
34	43*	-11
48	43*	-06
52	45*	05
55	48*	-02

Table 5

Kaiser Image Analysis on STVM III - 1

	Factor		
Item	I	II	III
5	20	-46	-01
6	17	-37	-00
24	27	-41	-10
32	33	-27	-11
34	32	-12	01
48	34	-17	-09
52	41	-27	01
55	41	-23	-02

Table 6

Little Jiffy on STVM III - 1

	Component	
Item	I	II
5	09	81
6	06	73
24	29	66
32	50	35
34	66	-05
48	64	08
52	62	28
55	67	19

Table 7

Jöreskog's Maximum Likelihood on STVM III - 1

	Factor	
Item	I	II
5	99	08
6	39	24
24	40	39
32	17	49
34	12	39
48	07	50
52	24	54
55	17	57

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Table 8

Regression of 26 letter vectors, 8 position vectors, and 1 part vector with item preferences of STVM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	32	21702.02	676.19	2.35	.01	.71
Error	31	8943.98	283.52			
Total	63	30646.00				

Table 9

Regression of 26 letter vectors and 8 position vectors with item preferences of STVM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	31	21516.30	694.07	2.43	.007	.70
Error	32	9129.70	285.30			
Total	63	30646.00				

Table 10

Regression of 26 letter vectors with item preferences of STVM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	24	10167.90	423.66	.81	.71	.33
Error	39	20478.10	525.08			
Total	63	30646.00				

Table 11

Regression of 8 position vectors with item preferences for STVM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	7	15239.75	2177.11	7.91	.0001	.50
Error	56	15406.25	275.11			
Total	63	30646.00				

Table 12

Regression analysis of 26 letter vectors, 8 position vectors, and 1 part vector with item preferences for STVM III

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	32	23410.35	731.57	2.64	.004	.73
Error	31	8592.64	277.18			
Total	63	32002.98				

Table 13

Regression analysis of 26 letter vectors and 8 position vectors with item preferences for STVM III

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	31	22615.82	729.54	2.49	.006	.71
Error	32	9387.17	293.35			
Total	63	32002.98				

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Table 14

Regression analysis of 26 letter vectors
with item preferences for STVM III

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	24	13412.46	558.85	1.17	.32	.42
Error	39	18590.52	476.68			
Total	63	32002.98				

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Table 15

Regression analysis of 8 position vectors
with item preferences of STVM III

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	7	14509.11	2072.73	6.64	.0001	.45
Error	56	17493.87	312.39			
Total	63	32002.98				

Table 16

Regression analysis of 9 color vectors, 6 position vectors, and 1 part vector on item difficulties of STCM I

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	14	11638.96	831.35	7.19	.0001	.72
Error	39	4509.85	115.64			
Total	53	16148.81				

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Table 17

Regression analysis of 9 color vectors and 6 position vectors on item preferences of STCM I

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	13	11502.87	884.84	7.62	.0001	.71
Error	40	4645.94	116.15			
Total	53	16148.81				

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Table 18

Regression analysis of 9 color vectors with item preference of STCM I

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	8	9263.66	1157.96	7.57	.0001	.57
Error	45	6885.16	153.00			
Total	53	16148.81				

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Table 19

Regression analysis of 9 color vectors, 6 position vectors, and 1 part vector with item preferences of STCM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	14	9564.44	683.17	7.64	.0001	.73
Error	39	3487.71	89.43			
Total	53	13052.15				

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Table 20

Regression analysis of 9 color vectors and 6 position vectors with item preferences for STCM II

Analysis of Variance

Source	df	SS	MS	F	P	R^2
Regression	13	8593.07	661.01	5.93	.0001	.66
Error	40	4459.07	111.48			
Total	53	13052.15				

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Table 21

Regression analysis of 9 color vectors and 1 part vector with item preferences for STCM II

Analysis of Variance

Source	df	SS	MS	F	p	R^2
Regression	9	8420.51	935.61	8.89	.0001	.64
Error	44	4631.64	105.26			
Total	53	13052.15				

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Table 22

Regression analysis of 6 position vectors and 1 part vector with item preferences for STCM II

Analysis of Variance

Source	df	SS	MS	F	p	R^2
Regression	6	2115.29	352.55	1.52	.19	.16
Error	47	10936.86	232.70			
Total	53	13052.15				

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STVM III - 1 correlation matrix

Item	2	3	4	5	6	7	8
1	40	43	21	15	11	28	21
2		26	20	10	16	23	19
3			36	13	25	24	30
4				19	30	33	21
5					21	30	26
6						21	32
7							40

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STVM II - 1 correlation matrix

Item	2	3	4	5	6	7	8
1	-07	10	16	05	-09	06	23
2		23	15	10	07	04	-02
3			19	06	09	01	02
4				07	05	03	06
5					18	24	29
6						24	13
7							25

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Intercorrelation matrix of item preference, part, 9 colors, and 6 positions for STCM I

Preference correlated with part, colors, and positions as follows (decimal points omitted):

-07, -13, 29, -01, 04, -57, 44, 02, 05, -13, 25, 08, 07, -17, -25, 03.

Part had zero correlation with all color and position variables except positions 5 and 6, which were -.06 and .06.

Colors 1-3, 5-7, and 9 intercorrelated -.12, correlated -.14 and -.11 with colors 4 and 8, and correlated zero with position vectors.

Colors 4 and 8 intercorrelated -.12. Color 4 correlated -.02 with all position vectors except 2, with which it correlated .12. Color 8 correlated .03 with all position vectors except 2, with which it correlated -.14.

Position vectors intercorrelated -.20.

Intercorrelation matrix of item preference part, 9 colors, and 6 positions for STCM II

Preference correlated with part, colors and positions as follows (decimal points omitted):

27, 24, -03, 14, -25, -33, 53, 00, -33, 01, 08, 15, 07, -14, -22, 06.

Part had zero correlations with all variables except preference.

All color vectors correlated -.12 with each other, and zero with position vectors.

All position vectors correlated -.20 with each other.

The 9 color vectors denoted, in order, gray, green, pink, red, purple, yellow, orange, blue, brown.

The 6 position vectors denoted, in order, positions 1-3, in the top row of the 2 x 3 stimulus matrix, and positions 4-6 of the bottom row.

Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM II

	part	A	B	C	D	E	F	G	H	I
Prefer	-08	17	18	-13	-09	-06	15	-12	-02	03
part		-17	-03	14	-02	20	12	08	-02	16
A			-04	-04	-06	-04	-05	-05	-06	-05
B				-01	-03	-02	-02	-02	-03	-02
C					-03	-02	-02	-02	-03	-02
D						-03	-04	-04	-05	-04
E							-02	-02	-03	-02
F								-03	-04	-03
G									-04	-03
H										-04

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM II (cont.)

	J	K	L	M	N	O	P	Q	R	S	T
prefer	-06	00	-19	12	-01	00	21	-03	-14	-10	-03
part	-13	00	-14	02	20	-01	20	20	-03	-09	04
A	-05	00	-08	-08	-05	-06	-04	-05	-05	-06	-05
B	-02	00	-04	-04	-02	-03	-02	-02	-02	-03	-02
C	-02	00	-04	-04	-02	-03	-02	-02	-02	-03	-02
D	-04	00	-06	-06	-04	-05	-03	-04	-04	-05	-04
E	-02	00	-04	-04	-02	-03	-02	-02	-02	-03	-02
F	-03	00	-05	-05	-03	-04	-02	-03	-03	-04	-03
G	-03	00	-05	-05	-03	-04	-02	-03	-03	-04	-03
H	-04	00	-06	-06	-04	-05	-03	-04	-04	-05	-04
I	-03	-00	-05	-05	-03	-04	-02	-03	-03	-04	-03
J		00	-05	-05	-03	-04	-02	-03	-03	-04	-03
K			00	00	00	00	00	00	00	00	00
L				-08	-05	-06	-04	-05	-05	-06	-05
M					-05	-06	-04	-05	-05	-06	-05
N						-04	-02	-03	-03	-04	-03
O							-03	-04	-04	-05	-04

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM II (cont.)

	Q	R	S	T
P	-02	-02	-03	-02
Q		-03	-04	-03
R			-04	-03
S				-04
T				
U				
V				
W				
X				
Y				

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM II (cont.)

	U	V	W	X	Y	Z	P1	P2	P3	P4	P5	P6	P7	P8
prefer	-11	02	15	-08	20	03	46	-16	05	29	-07	-41	-25	11
part	-24	-00	-03	12	-06	-04	00	00	00	00	00	00	00	00
A	-08	-08	-04	-05	-06	-06	-07	-11	-11	24	-11	24	-11	-11
B	-03	-03	-02	-02	-03	-03	-05	-05	-05	-05	-05	-05	-05	33
C	-03	-03	-02	-02	-03	-03	-05	-05	-05	-05	-05	33	-05	-05
D	-06	-06	-03	-04	-05	-05	14	-08	-08	-08	-08	14	14	-08
E	-03	-03	-02	-02	-03	-03	-05	-05	-05	-05	-05	-05	33	-05
F	-05	-05	-02	-03	-04	-04	20	-07	20	-07	-07	-07	-07	-07
G	-05	-05	-02	-03	-04	-04	-07	-07	-07	-07	-07	-07	-07	48
H	-06	-06	-03	-04	-05	-05	-08	-08	-08	-08	-08	14	14	14
I	-05	-05	-02	-03	-04	-04	-07	-07	20	20	-07	-07	-07	-07
J	-05	-05	-02	-03	-04	-04	-07	-07	20	-07	-07	-07	20	-07
K	00	00	00	00	00	00	00	00	00	00	00	00	00	00
L	-08	-08	-04	-05	-06	-06	-11	-11	07	07	24	-11	07	-11
M	-08	-08	-04	-05	-06	-06	07	07	-11	07	-11	07	07	-11
N	-05	-05	-02	-03	-04	-04	20	-07	-07	-07	20	-07	-07	-07
O	-06	-06	-03	-04	-05	-05	-08	-08	-08	14	14	-08	14	-08

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM II (cont.)

	U	V	W	X	Y	Z	P1	P2	P3	P4	P5	P6	P7	P8
P	-03	-03	-02	-02	-03	-03	33	-05	-05	-05	-05	-05	-05	-05
Q	-05	-05	-02	-03	-04	-04	-07	20	20	-07	-07	-07	-07	-07
R	-05	-05	-02	-03	-04	-04	-07	48	-07	-07	-07	-07	-07	-07
S	-06	-06	-03	-04	-05	-05	-08	36	-08	-08	14	-08	-08	-08
T	-05	-05	-02	-03	-04	-04	-07	20	-07	-07	20	-07	-07	-07
U		-07	-03	-05	-06	-06	10	-10	10	-10	10	10	10	-10
V			-03	-05	-06	-06	-06	10	-10	10	-10	-10	-10	10
W				-02	-03	-03	-05	-05	-05	33	-05	-05	-05	-05
X					-04	-04	-07	-07	20	-07	-07	20	-07	-07
Y						-05	-08	-08	-08	14	14	-08	-08	14
Z							-08	14	-08	-08	-08	-08	-08	36

The intercorrelations among the 8 position vectors are -.14.

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM III

	part	A	B	C	D	E	F	G	H	I
prefer	17	18	-04	12	01	-17	-09	00	-06	-04
part		12	-19	08	-00	-15	08	00	-15	-15
A			-03	-02	-03	-02	-03	00	-02	-02
B				-02	-03	-02	-03	00	-02	-02
C					-02	-02	-02	00	-02	-02
D						-02	-03	00	-02	-02
E							-02	00	-02	-02
F								00	-02	-02
G									00	00
H										-02
I										
J										
K										
L										
M										
N										
O										

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM III (cont.)

	J	K	L	M	N	O	P	Q	R	S	T
prefer	16	03	14	15	-07	-07	10	-10	14	-03	06
part	16	-10	24	-01	08	14	-11	-03	04	08	-10
A	-03	-05	-03	-05	-03	-02	-05	-02	-05	-03	-06
B	-03	-05	-03	-05	-03	-02	-05	-02	-05	-03	-06
C	-02	-04	-02	-04	-02	-02	-04	-02	-04	-02	-04
D	-03	-05	-03	-05	-03	-02	-05	-02	-05	-03	-06
E	-02	-04	-02	-04	-02	-01	-04	-02	-04	-02	-04
F	-03	-05	-03	-05	-03	-02	-05	-02	-05	-03	-06
G	00	00	00	00	00	00	00	00	00	00	00
H	-02	-04	-02	-04	-02	-02	-04	-02	-04	-02	-04
I	-02	-04	-02	-04	-02	-02	-04	-02	-04	-02	-04
J		-05	-03	-05	-03	-02	-05	-02	-05	-03	-06
K			-05	-08	-05	-04	-08	-04	-08	-05	-10
L				-05	-03	-02	-05	-02	-05	-03	-06
M					-05	-04	-08	-04	-08	-05	-10
N						-02	-05	-02	-05	-03	-06
O							-04	-02	-04	-02	-04
P								-04	-08	-05	-10
Q									-04	-02	-04
R										-05	-10
S											-06

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM III (cont.)

	U	V	W	X	Y	Z	P1	P2	P3	P4	P5
prefer	-33	-22	-08	16	-01	-16	11	-04	41	34	-27
part	-00	04	04	-18	-19	24	00	00	00	00	00
A	-03	-03	-03	-02	-04	-05	-07	-07	20	20	-07
B	-03	-03	-03	-02	-04	-05	-07	-07	-07	-07	20
C	-02	-02	-02	-01	-03	-04	-05	-05	33	-05	-05
D	-03	-03	-03	-02	-04	-05	-07	48	-07	-07	-07
E	-02	-02	-02	-01	-02	-04	-05	-05	-05	-05	-05
F	-03	-03	-03	-02	-04	-05	-07	-07	-07	-07	-07
G	00	00	00	00	00	00	00	00	00	00	00
H	-02	-02	-02	-02	-03	-04	-05	-05	-05	-05	33
I	-02	-02	-02	-02	-03	-04	33	-05	-05	-05	-05
J	-03	-03	-03	-03	-04	-05	-07	-07	-07	20	-07
K	-05	-05	-05	-04	-06	-08	-11	-11	-11	24	-11
L	-03	-03	-03	-02	-04	-05	-07	-07	-07	-07	20
M	-05	-05	-05	-04	-06	-08	42	-11	-11	07	07
N	-03	-03	-03	-02	-04	-05	-07	20	-07	-07	20
O	-02	-02	-02	-02	-02	-03	-05	-05	-05	-05	33

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM III (cont.)

	U	V	W	X	Y	Z	P1	P2	P3	P4	P5
P	-05	-05	-05	-04	-06	-08	-11	-11	24	07	-11
Q	-02	-02	-02	-02	-03	-04	-05	33	-05	-05	-05
R	-05	-05	-05	-04	-06	-08	07	07	-11	24	-11
S	-03	-03	-03	-02	-04	-05	20	-07	-07	-07	20
T	-06	-06	-06	-04	-08	-10	02	17	17	-13	-13
U		-03	-03	-02	-04	-05	-07	-07	-07	-07	-07
V			-03	-02	-04	-05	20	-07	-07	-07	-07
W				-02	-04	-05	-07	-07	-07	-07	-07
X					-03	-04	-05	-05	33	-05	-05
Y						-06	-08	14	-08	-08	14
Z							-11	-11	07	-11	-11

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Intercorrelations among item preferences, part, letter vectors, and position vectors for STVM III (cont.)

	P6	P7	P8
prefer	-29	-01	-25
part	00	00	00
A	-07	-07	-07
B	-07	20	-07
C	-05	-05	-05
D	-07	-07	-07
E	-05	-05	33
F	-07	-07	48
G	00	00	00
H	-05	-05	-05
I	-05	-05	-05
J	-07	20	-07
K	07	07	07
L	-07	20	-07
M	-11	-11	-11
N	-07	-07	-07

	P6	P7	P8
O	-05	-05	-05
P	07	07	-11
Q	-05	-05	-05
R	07	-11	-11
S	-07	-07	-07
T	-13	02	02
U	20	20	-07
V	-07	-07	20
W	20	20	-07
X	-05	-05	-05
Y	-08	-08	14
Z	42	-11	07

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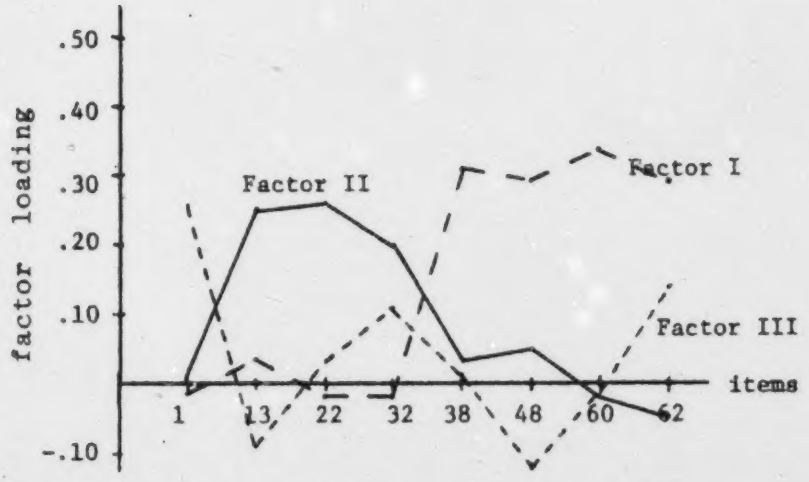

Figure 1

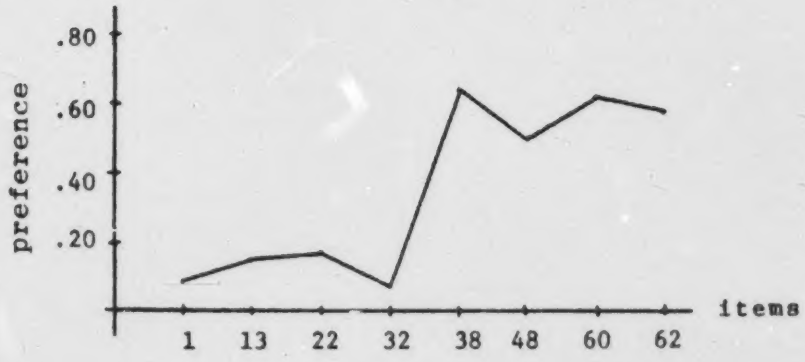

Figure 2

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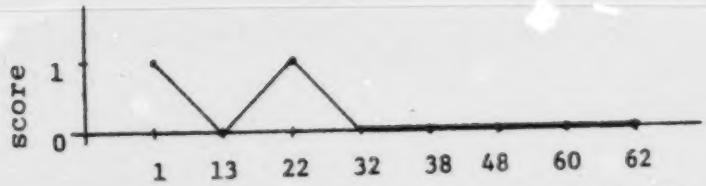
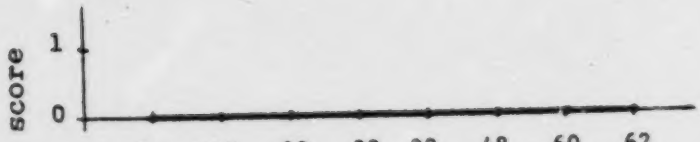


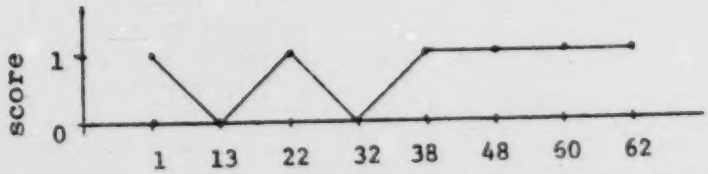
S 15; factor scores = 35, 57, 66

Figure 3



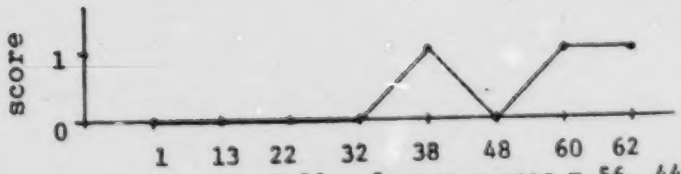
S 19; factor scores = 31, 41, 41

Figure 4



S 21; factor scores = 66, 63, 76

Figure 5



S 56; factor scores = 56, 44, 54

Figure 6

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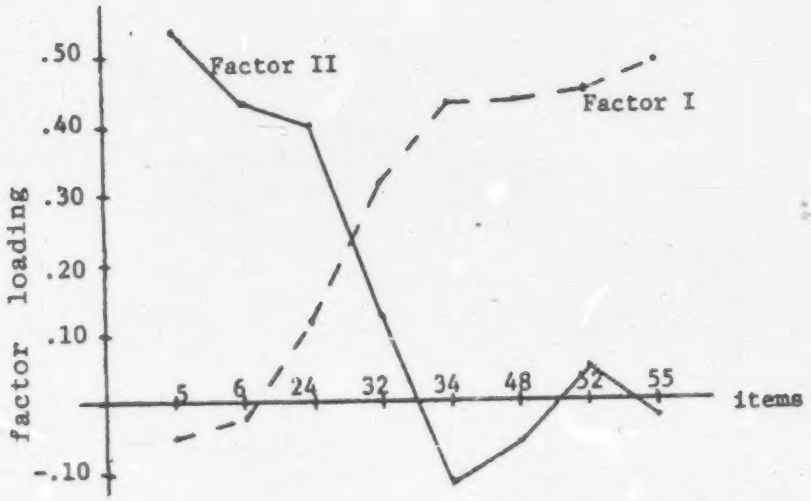


Figure 7

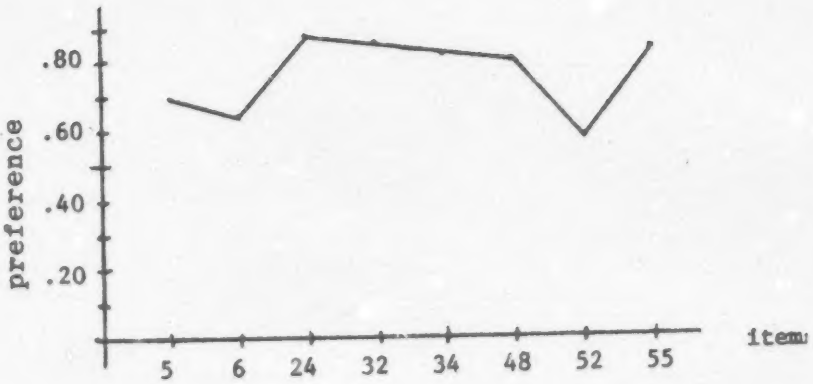
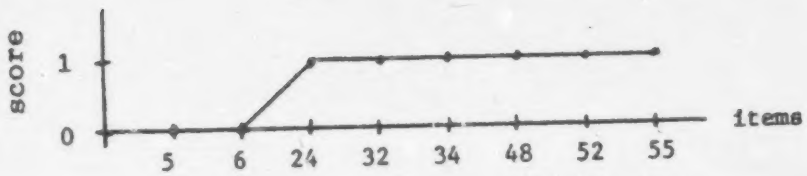


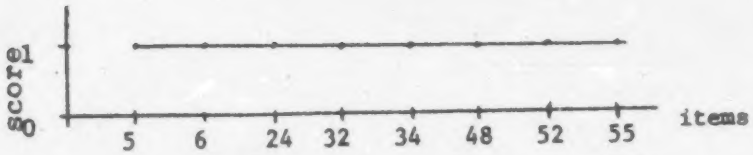
Figure 8

BEST COPY AVAILABLE



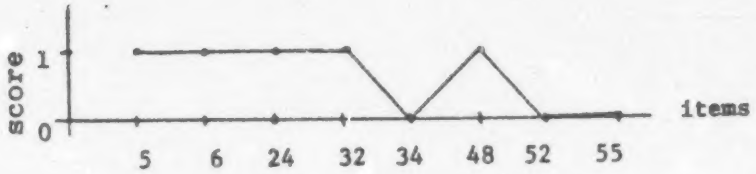
S 30; factor scores = 54, 44

Figure 9



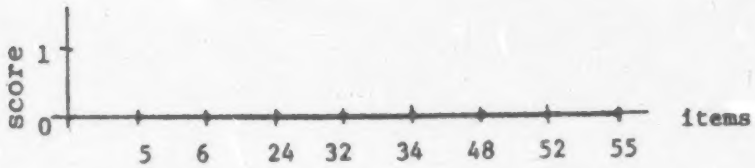
S 111; factor scores = 59, 59

Figure 10



S 152; factor scores = 39, 52

Figure 11



S 155; factor scores = 17, 20

Figure 12

Appendix

Short Term Color Memory I: Ss first shown a stimulus pool of nine hexagonal color chips (a red, green, purple, yellow, orange, brown, gray, pink and blue). After these are presented and named, the 54 items of the test then present the color chips in a 2 by 3 array, holding the array on the screen either for the duration of 4, 8, or 12 frames. There are thus three 18-items subtests, each with a different stimulus exposure duration. In each item, after the array disappears, there are two blank film frames, then an empty hexagonal marker appears in one of the array positions. The Ss are to indicate the color which occupied the marked array position.

Short Term Color Memory II: This film test is similar to STCM I. It differs in that it marks the color to be remembered by following the array with a horizontal colored bar in the center of the screen. The Ss are then to indicate the position occupied by the color.

Short Term Visual Memory II: A film test of 64 items which includes eight eight-item subtests. In each item an eight letter, 2 by 4 array is presented tachistoscopically (i.e., for about 31 milliseconds) in screen center. A black circle marker appears to mark one of the eight array positions and Ss are to record the letter occupying the designated position. The circle marker may precede the array by 52 milliseconds or may follow it by 10, 94, 177, 260, 344, 428, or 510 milliseconds.

Short Term Visual Memory III: This film test is highly similar to STVM II, except that it employs two markers to designate the same array position in each test item. Not only does a circle marker appear as in STVM II, but also simultaneously with each 2 by 4 array, a black vertical bar marker appears.